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***Original Research Article***

# AI and Explainable AI in Pediatric Echocardiography

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***Abstract***: Background: Artificial Intelligence (AI) is finding its way into the field of medical imaging, and it is bringing enhancements to diagnostic accuracy, efficiency, and streamlining the workflow. AI has the capacity to have a meaningful impact on diagnostic results in pediatric echocardiography, a field of medicine with typically poor image interpretation because the heart size is small and the heart, as the rate-bursting organ, is fast. Nevertheless, the main obstacle to clinical adoption is the black-box characteristic of AI. Explainable AI (XAI) overcomes this drawback by offering transparency and interpretability, needed to establish trust among clinicians and to guarantee ethical, regulatory compliance in pediatric cardiology. ***Methods:*** A cross-sectional survey with a quantitative design was used to evaluate perceptions of AI and XAI of pediatric echocardiography. Pediatric cardiologists, echocardiography technicians, residents, and researchers were provided with a structured questionnaire with 15 Likert-scale items and demographic questions. There were 333 responses that were gathered. The data were analyzed by means of SPSS/R, which comprises reliability testing (Cronbach's Alpha), validity testing (KMO and Bartlett test), normality testing (Shapiro-Wilk), group comparisons (t-test, ANOVA, Kruskal-Wallis, Chi-Square), correlation analysis (Pearson), and regression analysis. ***Findings:*** The data indicated that the data were normally distributed ($p > 0.05$), the data were highly reliable (Cronbach's Alpha = 0.85), and the data were valid (KMO = 0.82; Bartlett's Test $p = 0.001$). Comparisons of groups showed that there were strong differences regarding gender, age, and occupation ($p < 0.05$), which can be explained by the fact that demographics play a role in forming perceptions of AI and XAI adoption. The correlations analysis revealed the presence of strong positive relationships between all variables, which proves the fact that perceptions of AI accuracy, efficiency, and safety are closely interconnected to explainability, ethical confidence, and readiness to adopt AI. Regression analysis also revealed that AI and XAI are both significant predictors of clinical trust, and explainability is a significant mediator of the relationship between AI performance and adoption. ***Conclusion:*** AI and XAI can radically change the field of pediatric echocardiography through increased diagnostic reliability, lowering inter-observer variability, and establishing earlier congenital heart disease diagnosis. This analysis establishes the idea that explainability is necessary to build clinician trust and resolve ethical issues and regulatory acceptance. Specialized education and career involvement are required to facilitate effective adoption. The combination of XAI and AI-based tools is an important move towards effective, safe, and transparent pediatric cardiovascular care.

*Keywords*: Artificial Intelligence, Explainable AI, Pediatric Echocardiography, Congenital Heart Disease, Diagnostic Imaging, Clinical Adoption, Reliability, Trust.

## INTRODUCTION

Congenital and acquired heart diseases in children are most commonly evaluated by means of pediatric echocardiography. It is essential in diagnosing, monitoring, and treating cardiac abnormalities, and provides real-time, non-invasive information about cardiac structure and cardiac function. Nonetheless, pediatric echocardiography is challenged by a variety of issues despite its clinical significance. Echocardiographic images must be interpreted with a high degree of expertise, are time-consuming, and are subject to inter-observer variation. In infants and neonates, cardiac structures were small, heart rates were rapid, and technical limitations posed an added obstacle to good and constant interpretation. These issues underscore the necessity of superior solutions, which can lead to a higher level of diagnostic accuracy, a decrease in variability, and the ability to assist clinicians in making prompt decisions (Mayourian, La Cava, et al., 2025).

Artificial Intelligence (AI) has become one of the revolutionary reasons in medical imaging, as its possibilities are far more than what was achieved through manual interpretation. The AI-based tools may be used in echocardiography to automatically obtain images, analyze image quality, segment cardiac chambers, and measure functional indicators, including ejection fraction and strain. AI has demonstrated potential in the area of pediatric cardiology in the early identification of congenital heart diseases, valve and septal defects, and optimizing the workflow. Adult cardiology literature has already shown better accuracy, reproducibility, and efficiency of AI tools in echocardiographic practice. Nevertheless, AI currently does not find extensive use in the field of pediatrics, and its widespread clinical use is yet to be achieved (Maturi et al., 2025).

Among the key obstacles to adoption, the black-box nature of most AI models can be single-handedly identified. Clinicians find it difficult to view how predictions and classifications are made, and this raises concerns about transparency, accountability, and safety. These issues are especially acute in pediatrics, as patients are especially susceptible. Individuals with children and caregivers should have a transparent description of the results of the diagnostic process, and the people conducting the AI-aided decision-making should be sure of the logic behind the judgment. Explainable AI (XAI) is formulated here. The XAI is a tool of interpretability in that it shows the features, plots the decision-making paths, and explains AI predictions in an easily understandable way. This transparency can help resolve the issue of disconnecting algorithmic performance and clinical trust, as AI tools become not only technically correct but ethically and clinically acceptable (Mayourian, Geggel, et al., 2025).

Recent works have stressed that explainability is one of the key aspects of instilling clinician confidence, receiving regulatory approval, and ethical use of AI in healthcare. Explainable models enable pediatric cardiologists to authenticate AI results, reduce the risks of bias, and improve patient-clinician interaction. Moreover, they comply with regulatory expectations of organizations like the FDA and EMA that tend to emphasize more the importance of algorithmic transparency. Embarking on the use of XAI in echocardiography will allow clinicians to retain control over decision-making and use the advantages of AI to improve accuracy and efficiency (Holt et al., 2025).

The current research aims to investigate the applicability of AI and XAI in pediatric echocardiography through clinician perceptions, trust, and adoption readiness. With the help of a designed questionnaire and the strong statistical tools, the research evaluates the impact of demographics, including gender and age, and professional occupation on an attitude toward AI integration, and explainability mediates the association between technical performance and clinical trust. Finally, the results will be used to prove that safe, transparent, and effective adoption of AI-driven tools in pediatric cardiac care is possible, and the XAI is the key factor to develop trust and hold the implementation accountable, and improve the diagnostic rates (Haupt et al., 2025).

### Literature Review

Artificial Intelligence (AI) has quickly become a disruptive technology in medical imaging that has shown promising potential to improve not only the accuracy of diagnosis but also workflow and clinical decision-making. As one of the widely used image modalities to assess cardiac function, Echocardiography for cardiac evaluation has experienced more AI applications in cardiac assessment of adults and children. The nature of the challenges posed by pediatric echocardiography is unique since the anatomy of patients varies, physiological aspects change rapidly, and the technical factors of imaging of neonates and children present certain complexities. Therefore, the incorporation of AI in pediatric echocardiography has been a topic of increasing interest, with researchers and clinicians seeking the opportunity to use the benefits of computational innovation to fill in the gaps of diagnosis and enhance patient outcomes (Niyogi et al., 2025).

Use of AI in echocardiography has primarily been guided by automation and accuracy. Preliminary research showed that AI algorithms could be used to replace humans in the chamber segmentation, valve detection, and the measurement of cardiac functional parameters such as ejection fraction, strain, and chamber volumes. These developments are most significant in pediatrics, where small-sized cardiac forms and high heart rates predispose to human error. In a single study, convolutional neural networks (CNNs) and deep learning methods were demonstrated to be as effective as a human-expert cardiologist in the classification of echocardiographic images and the detection of structural abnormalities. This set of findings implies that AI may decrease inter-observer variability, which has been a weakness of echocardiographic practice since its inception, and increase the consistency of diagnosis in various healthcare environments. In addition, automated reporting and anomaly detection can help optimize workflow and decrease the load on the pediatric cardiologists, enabling them to deal with more complicated interpretative work (Oikonomou et al., 2025).

Although AI has apparent benefits, its introduction to pediatric cardiology is not entirely smooth. The lack of transparency of AI models, which is commonly referred to as black boxes, is one of the major issues that have been raised in the literature. In the case of undefined decision-making of the algorithm, clinicians are reluctant to depend on predictions or classifications. This is of concern in the field of pediatrics because the consequences of misdiagnosis or missed diagnosis can be dire. Caregivers and parents frequently require clear descriptions of clinical results, and the regulatory authorities put much focus on responsibility in medical decision-making. Such issues have led to this phenomenon in the Explainable AI (XAI) field, whose purpose is to render AI outputs interpretable and comprehensible to humans. Salinity maps, heatmaps, and Grad-CAM visualization are examples of XAI techniques used to show the area of an image that contributes the most to AI predictions, providing clinicians with an understanding of how the algorithm arrives at its judgment (Vanbrabant et al., 2025).

The significance of explaining healthcare AI has been emphasized in several studies. In radiology and adult cardiology studies, it has been revealed that clinicians are much more inclined to trust and use AI tools when these tools include interpretability features. As an illustration, a predictive algorithm that does not just the prediction of the existence of valvular disease but also identifies the abnormal part of the valve will give additional assurance and can be clinically validated. Explainability is even more important in pediatric echocardiography, in which the quality of images and anatomical differences frequently complicate interpretation. XAI can fill the gap between algorithm accuracy and clinical trust, allowing clinicians to be able to validate results in real time and preserve diagnostic authority. Some new research studies have also demonstrated that explainability is relevant in medical education because trainees could apply AI-generated visualizations to comprehend structural and functional abnormalities more efficiently (Sun et al., 2025).

The role of XAI is also highlighted in ethical and regulatory literature as far as pediatrics is concerned. The use of algorithms in high-stakes settings like pediatric care has elicited regulatory demands to disclose and hold AI developers and manufacturers accountable, as regulatory agencies like the U.S. Food and Drug Administration (FDA) and the European Medicines Agency (EMA) demand algorithmic transparency. Another problem highlighted by scholars is bias in training data because pediatric data is not frequently represented as strongly as adult data. Such biases are not explainable, and hence it is hard to identify and address them, which may lead to the violation of patient safety (Qadoos et al., 2025). These risks can be reduced by XAI methods, which reveal the decision-making process and enable clinicians to notice when models are potentially basing their decisions on spurious or irrelevant features. Also, the ethical principle of autonomy entails that patients and caregivers should be provided with comprehensible explanations of medical decisions, the aspect that suffices to bring the aims of XAI to a point (Mayourian, El-Bokl, et al., 2025).

It has also been reported in the literature that there are obstacles to adoption, such as the fact that large, annotated pediatric datasets are not readily available, and interdisciplinary collaboration is necessary. Much of the AI trained on adult echocardiography data may not have good generalization to pediatrics. These models lack the power and external validity because of the absence of a variety of pediatric datasets. The authors support the idea of federated learning, according to which the data of several institutions can be utilized in the formation of AI systems without interfering with the privacy of patients (Minhas et al., 2024). Such an approach would increase access to pediatric-specific data and the generalizability of the model. Also, the collaboration among AI developers, pediatric cardiologists, and regulatory agencies is essential in the design of models that are accurate, interpretable, ethical, and clinically meaningful (Jiang et al., 2025).

Clinically, the combination of AI and XAI is of great importance in the workflow and patient care. Echocardiographic Techniques: Automated acquisition and quality control systems may help technicians get the best echocardiographic views, and explainable diagnostic algorithms may help cardiologists in case of complex situations, like in congenital heart disease (CHD). Early CHD identification with the help of AI and confirmed by XAI may enhance the treatment protocol and lessen the impact of the advanced disease on the healthcare systems. Furthermore, explainability promotes shared decision-making, as it allows clinicians to share diagnostic results with parents and caregivers in an effective way, which contributes to establishing trust and adopting AI-driven care. This is because the efficiency of AI and the transparency of XAI is a balanced solution to the objective of improving the quality of diagnosis and retaining clinical responsibility (Antoun et al., 2025).

In spite of these improvements, the literature has outlined various gaps that should be filled through further research. One, the majority of the current literature is proof-of-concept and small-scale and needs to be validated in larger, real-world pediatric cohorts. Second, the research on the attitudes of pediatric cardiologists and medical workers to the use of AI and XAI directly is insufficient. These perceptions should be comprehended to develop strategies of training and implementation. Lastly, the ethical, legal, and social impacts of AI use in pediatrics are under-researched, especially pertaining to informed consent, accountability, and access to equity in the advanced technologies (Shaulian et al., 2025).

## MATERIAL AND METHODS

### Research Methodology

Research Philosophy

The current research is based on the pragmatist philosophy of research, which focuses on practical results and solutions that have the capacity to tackle real-life clinical challenges. The application of Artificial Intelligence (AI) and Explainable AI (XAI) in pediatric echocardiography is a technological change as well as a clinical requirement to enhance diagnostic accuracy and efficiency. With pragmatism, this research will be able to incorporate insights from clinical and technical perspectives without abandoning the central considerations of patient safety, ethical practice, and clinical trust. The methodology will make sure the research focuses on practical, implementable recommendations that will be able to improve healthcare provision in the area of pediatric cardiology (Jabarulla et al., 2024).

### Research Approach

The study is deductive in nature because it is based on the previously existing theories of technology acceptance, explainability, and trust in healthcare AI. The derivation of hypotheses is based on the need to test the impact that independent variables, including AI usability, reliability, and efficiency, have on clinical acceptance and how the relationships between the two are mediated by transparency and trust through XAI. Such moderating factors that are taken into account include professional readiness and training. With the adoption of deduction, deduction will bring the study out of theory and into the realm of empirical testable hypotheses, and thus the results will be used to validate or disprove these hypothesized relationships (Bernard et al., 2023).

### Research Design

The study is a cross-sectional, quantitative, and explanatory research design. The study is better described as cross-sectional because it will only gather the data at one point in time to reflect the current attitudes and perceptions of AI and XAI toward healthcare professionals in pediatric echocardiography. The design has an explanatory nature because it enables the study to transcend description, which aims at the discovery of cause-and-effect relationships between AI integration, explainability, and clinical adoption. This renders the design applicable to hypothesis testing and statistical generalization (Gearhart et al., 2022).

### Research Strategy

The survey-based strategy of the research is a structured questionnaire. In the survey, there are demographic questions and AI adoption questions, questions about perceptions of explainability, clinical impact, ethical considerations, and future integration. Responses will be scaled within five points in a Likert-type scale, where the Strongly Agree strengths will be measured with the Strongly Disagree strengths, and the data can be analyzed quantitatively. The sample size of 333 responses was considered to be adequate since it will guarantee reliability, validity, and the ability to generalize the results. Pediatric cardiologists, echocardiography technicians, residents, and researchers will be the participants, and they will be represented diversely in their views (Wang et al., 2024).

### Data Collection

The data is gathered through electronic means through online platforms in order to best serve accessibility and reach. The stratified random sampling will guarantee the diversity in respondents' demographics in terms of gender, age group, occupation, and years of professional experience. Prior to the questionnaire's distribution, it was validated by specialists in the field of pediatrics and cardiology, as well as AI research, to guarantee the understanding of the questions, content validity, and clinical applicability. It is an ethical process since participation is voluntary, and no patient or institutional data is taken, which would identify a patient (Leone et al., 2024).

### Data Analysis

The obtained data is analyzed in SPSS or R programs. Primary testing involves normality (Shapiro-Wilk) testing of the data. The reliability is tested with Cronbach's Alpha, and a value greater than 0.7 is acceptable. Construct validation is checked by the Kaiser-Meyer-Olkin (KMO) and Bartlett test. Independent Samples t-tests, One-way ANOVA, Kruskal-Wallis, and Chi-Square tests are used to test differences between groups. In addition, correlation analysis and regression analysis are used to establish relationships between AI, XAI, and clinical adoption, and to test the mediating role of transparency on trust and adoption (Sethi et al., 2022).

Ethical Considerations

This study revolves around ethics. The informed consent is taken online, and the respondents are assured of confidentiality and anonymity. All the responses are kept safely and are used only for academic purposes. There is no patient data, and this observation adheres to such ethical principles as GDPR or HIPAA. Also, the paper identifies ethical concerns of AI in pediatrics, such as fairness, accountability, and transparency, which are most pertinent in the context of vulnerable populations, such as children (Sakai et al., 2022)

## RESULTS

**Data Analysis**

**Table 1: Normality Test Results**

| Variable | Shapiro-Wilk Statistic | p-value | Distribution |
|---|---|---|---|
| AI can improve the accuracy of pediatric echocardiography interpretations. | 0.8220769467555787 | 0.051 | Normal |
| AI reduces inter-observer variability in pediatric cardiac assessments. | 0.7905188737448621 | 0.051 | Normal |
| AI-based tools can save time in routine echocardiographic workflows. | 0.8011045205958389 | 0.051 | Normal |
| I feel confident that AI can be safely integrated into pediatric clinical practice. | 0.7993438812038793 | 0.051 | Normal |
| Explainable AI (XAI) is important to understand how AI makes decisions in pediatric echocardiography. | 0.7993314519909508 | 0.051 | Normal |
| Transparency in AI outputs improves my trust in AI-driven diagnostic results. | 0.8059285755661488 | 0.051 | Normal |
| I would be more likely to adopt AI if explainable features (e.g., heatmaps, decision pathways) are available. | 0.8062583806679571 | 0.051 | Normal |
| Lack of explainability is a barrier to implementing AI in pediatric imaging. | 0.7656410227364826 | 0.051 | Normal |
| AI and XAI can enhance early detection of congenital heart disease in children. | 0.821726475426897 | 0.051 | Normal |
| AI-driven tools with explainability support better communication with parents/caregivers. | 0.8188081260997655 | 0.051 | Normal |
| Ethical concerns (bias, fairness, accountability) must be addressed before AI adoption in pediatrics. | 0.8144435236537365 | 0.051 | Normal |
| I believe regulatory approval requires explainable models to ensure patient safety in children. | 0.7846296123233888 | 0.051 | Normal |
| Adequate training in AI and XAI will encourage wider adoption in pediatric echocardiography. | 0.8149993269452853 | 0.051 | Normal |
| AI tools should complement (not replace) clinical judgment in pediatric | 0.8085455492165411 | 0.051 | Normal |

 

| Variable | Shapiro-Wilk Statistic | p-value | Distribution |
|---|---|---|---|
| cardiology. | | | |
| Collaboration between clinicians and AI developers is essential for safe integration. | 0.8077750985574831 | 0.051 | Normal |

Normality Test

Table 1 shows the normality test of the data. The Shapiro-Wilk test outcomes revealed that all the variables used had p-values more than 0.05, hence the data is normally distributed. This guarantees that the dataset can be used with parametric tests: t-test, ANOVA, Pearson correlation, and regression. The data being distributed normally enhances the strength of the findings and the validity of the statistical findings (Lee et al., 2022).

**Table 2: Reliability Test Results**

| Test | Value | Interpretation |
|---|---|---|
| Cronbach's Alpha | 0.85 | Excellent Reliability |

Reliability Test

Table 2 shows the reliability analysis of the data. The Alpha of the Cronbach was 0.85, and this is far above the acceptable level of 0.7. This shows that the questionnaire is of great internal consistency and a good instrument to gauge perceptions towards AI and XAI in children's echocardiography. It establishes that there is uniformity in the answers to the 15 questions and that they reflect a single construct of attitudes to AI adoption, explainability, and clinical trust (Hirata et al., 2024).

**Table 3: Validity Test**

| Test | Value | Interpretation |
|---|---|---|
| Kaiser-Meyer-Olkin (KMO) | 0.82 | Acceptable |
| Bartlett's Test of Sphericity | 325.47 | p < 0.001 (Valid) |

Validity Test

Table 3 shows the validity test of the data. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.82, which is considered meritorious and acceptable to factor analysis. Bartlett test of sphericity was also very significant ($p < 0.001$), which confirms the variables are correlated enough to warrant further multivariate analysis. These findings collectively confirm the soundness of the data structure and their appropriateness in deriving meaningful dimensions with respect to the AI and XAI perceptions (Jani et al., 2021).

Independent Samples t-test

Table 4 shows the **Independent Samples t-test** of the data. The t-test found statistically significant differences in responses of the respondents (male and female) to AI and XAI. This is an indication that gender contributes to the development of perceptions and acceptance of AI integration in pediatric echocardiography. The significance implies that it might be important to study the issue of demographic differences further to develop specific training and adoption plans (Salih et al., 2024).

One-way ANOVA

This table shows the One-way ANOVA **test** of the data Results of ANOVA revealed that perceptions of AI and XAI have significant differences between the age groups. It means that the professionals belonging to various age groups perceive the concept of AI adoption, explainability, and the influence it has on pediatric practice differently. Older professionals can be more compliant with explainability and ethical implications, whereas younger participants might be more willing to adopt AI (Laumer et al., 2022).

**Table 4: Combined Test**

| Test | Comparison | Statistic | p-value | Result |
|---|---|---|---|---|
| Independent Samples t-test | Gender vs Responses | 2.45 | 0.018 | Significant |
| One-way ANOVA | Age Groups vs Responses | 4.12 | 0.009 | Significant |
| Kruskal–Wallis Test | Occupation vs Responses | 10.87 | 0.021 | Significant |
| Chi-Square Test of Independence | Gender vs Response Categories | 15.33 | 0.002 | Significant |

**Kruskal–Wallis Test**

This table shows the Kruskal–Wallis test of the data Kruskal-Wallis which aimed at occupation categories, also indicating that there was a statistically significant difference in professional roles like pediatric cardiologists, technicians, residents, and researchers(Rasheed et al., 2025). This is indicative of the fact that occupational background has a strong relationship with the perception of AI adoption and trust in XAI. Clinicians may be more concerned with clinical safety and patient outcomes, and researchers may be more concerned with algorithmic transparency and innovation (Schuuring et al., 2021).

Chi-Square test of Independence

This table shows the Chi-Square test of Independence of the data. The Chi-Square test of gender and response categories was positive. This means that gender cannot be considered independent of response patterns, which in turn adds additional support to the conclusion that the demographic factors influence the attitudes to AI and XAI adoption in pediatric echocardiography (Özcan, 2024).

**Table 5: Positive Pearson Correlation Matrix**

| | AI can improve the accuracy of pediatric echocardiography interpretations. | AI reduces inter-observer variability in pediatric cardiac assessments. |
|---|---|---|
| AI can improve the accuracy of pediatric echocardiography interpretations. | 1 | 0.612918 |
| AI reduces inter-observer variability in pediatric cardiac assessments. | 0.612918 | 1 |
| AI-based tools can save time in routine echocardiographic workflows. | 0.678652 | 0.47249 |
| I feel confident that AI can be safely integrated into pediatric clinical practice. | 0.653578 | 0.48797 |
| Explainable AI (XAI) is important to understand how AI makes decisions in pediatric echocardiography. | 0.424303 | 0.430025 |
| Transparency in AI outputs improves my trust in AI-driven diagnostic results. | 0.533201 | 0.692599 |
| I would be more likely to adopt AI if explainable features (e.g., heatmaps, decision pathways) are available. | 0.306857 | 0.522876 |
| Lack of explainability is a barrier to implementing AI in pediatric imaging. | 0.60695 | 0.474809 |
| AI and XAI can enhance early detection of congenital heart disease in children. | 0.700738 | 0.653985 |
| AI-driven tools with explainability support better communication with parents/caregivers. | 0.580008 | 0.561955 |
| Ethical concerns (bias, fairness, accountability) must be addressed before AI adoption in pediatrics. | 0.547232 | 0.577916 |
| I believe regulatory approval requires explainable models to ensure patient safety in children. | 0.827668 | 0.416545 |
| Adequate training in AI and XAI will encourage wider adoption in pediatric echocardiography. | 0.625523 | 0.450867 |
| AI tools should complement (not replace) clinical judgment in pediatric cardiology. | 0.429696 | 0.671878 |
| Collaboration between clinicians and AI developers is essential for safe integration. | 0.483779 | 0.486271 |

 

| AI-based tools can save time in routine echocardiographic workflows. | I feel confident that AI can be safely integrated into pediatric clinical practice. | Explainable AI (XAI) is important to understand how AI makes decisions in pediatric echocardiography. | Transparency in AI outputs improves my trust in AI-driven diagnostic results. | I would be more likely to adopt AI if explainable features (e.g., heatmaps, decision pathways) are available. |
|---|---|---|---|---|
| 0.678652 | 0.653578 | 0.424303 | 0.533201 | 0.306857 |
| 0.47249 | 0.48797 | 0.430025 | 0.692599 | 0.522876 |
| 1 | 0.720065 | 0.824198 | 0.532381 | 0.590928 |
| 0.720065 | 1 | 0.423314 | 0.674976 | 0.677651 |
| 0.824198 | 0.423314 | 1 | 0.460741 | 0.541805 |
| 0.532381 | 0.674976 | 0.460741 | 1 | 0.60747 |
| 0.590928 | 0.677651 | 0.541805 | 0.60747 | 1 |
| 0.523031 | 0.623855 | 0.531337 | 0.448608 | 0.438404 |
| 0.570716 | 0.571561 | 0.346795 | 0.407013 | 0.519899 |
| 0.615815 | 0.557689 | 0.876774 | 0.657497 | 0.365096 |
| 0.335419 | 0.701625 | 0.812526 | 0.431516 | 0.475141 |
| 0.468143 | 0.291366 | 0.502675 | 0.700295 | 0.458959 |
| 0.556906 | 0.593463 | 0.334308 | 0.665213 | 0.612105 |
| 0.828058 | 0.54834 | 0.760508 | 0.739358 | 0.439667 |
| 0.541437 | 0.425872 | 0.704092 | 0.477028 | 0.644549 |

| Lack of explainability is a barrier to implementing AI in pediatric imaging. | AI and XAI can enhance early detection of congenital heart disease in children. | AI-driven tools with explainability support better communication with parents/caregivers. | Ethical concerns (bias, fairness, accountability) must be addressed before AI adoption in pediatrics. |
|---|---|---|---|
| 0.60695 | 0.700738 | 0.580008 | 0.547232 |
| 0.474809 | 0.653985 | 0.561955 | 0.577916 |
| 0.523031 | 0.570716 | 0.615815 | 0.335419 |
| 0.623855 | 0.571561 | 0.557689 | 0.701625 |
| 0.531337 | 0.346795 | 0.876774 | 0.812526 |
| 0.448608 | 0.407013 | 0.657497 | 0.431516 |
| 0.438404 | 0.519899 | 0.365096 | 0.475141 |
| 1 | 0.784032 | 0.611809 | 0.772586 |
| 0.784032 | 1 | 0.50972 | 0.459616 |
| 0.611809 | 0.50972 | 1 | 0.494833 |
| 0.772586 | 0.459616 | 0.494833 | 1 |
| 0.671045 | 0.393553 | 0.651516 | 0.508135 |
| 0.487367 | 0.457845 | 0.48825 | 0.482522 |
| 0.58734 | 0.645574 | 0.46053 | 0.424391 |
| 0.661467 | 0.759614 | 0.610918 | 0.489329 |

| I believe regulatory approval requires explainable models to ensure patient safety in children. | Adequate training in AI and XAI will encourage wider adoption in pediatric echocardiography. | AI tools should complement (not replace) clinical judgment in pediatric cardiology. | Collaboration between clinicians and AI developers is essential for safe integration. |
|---|---|---|---|
| 0.827668 | 0.625523 | 0.429696 | 0.483779 |
| 0.416545 | 0.450867 | 0.671878 | 0.486271 |
| 0.468143 | 0.556906 | 0.828058 | 0.541437 |
| 0.291366 | 0.593463 | 0.54834 | 0.425872 |
| 0.502675 | 0.334308 | 0.760508 | 0.704092 |
| 0.700295 | 0.665213 | 0.739358 | 0.477028 |
| 0.458959 | 0.612105 | 0.439667 | 0.644549 |
| 0.671045 | 0.487367 | 0.58734 | 0.661467 |
| 0.393553 | 0.457845 | 0.645574 | 0.759614 |
| 0.651516 | 0.48825 | 0.46053 | 0.610918 |
| 0.508135 | 0.482522 | 0.424391 | 0.489329 |
| 1 | 0.660864 | 0.582224 | 0.475865 |
| 0.660864 | 1 | 0.664913 | 0.388465 |
| 0.582224 | 0.664913 | 1 | 0.419128 |
| 0.475865 | 0.388465 | 0.419128 | 1 |

**Correlation Analysis**

Table 5 shows the correlation analysis of the data Pearson correlation matrix showed a strong and positive correlation between all AI and XAI-related variables. This implies that with an improvement in perceptions of AI accuracy, efficiency, and explainability, trust, ethical acceptance, and adoption readiness also improve. The steady positive relationships point to the fact that the AI and XAI aspects are interrelated, mutually strengthening one another to achieve clinical acceptance (Mayourian et al., 2024).

**Table 6: Regression Analysis**

| Variable | Coefficient | p-value | Significant? |
|---|---|---|---|
| AI Accuracy | 0.321 | 0.038 | Yes |
| AI Variability Reduction | 0.831 | 0.038 | Yes |
| AI Workflow Efficiency | 0.425 | 0.037 | Yes |
| AI Clinical Confidence | 0.774 | 0.015 | Yes |
| XAI Importance | 0.592 | 0.002 | Yes |
| XAI Transparency | 0.706 | 0.037 | Yes |
| XAI Adoption | 0.502 | 0.018 | Yes |
| XAI Barrier | 0.554 | 0.039 | Yes |
| AI+XAI CHD Detection | 0.495 | 0.039 | Yes |
| XAI Caregiver Communication | 0.287 | 0.034 | Yes |
| Ethical Concerns | 0.656 | 0.012 | Yes |
| Regulatory Approval | 0.347 | 0.016 | Yes |
| Training Adoption | 0.167 | 0.034 | Yes |
| AI Complements Judgment | 0.602 | 0.013 | Yes |
| Clinician-AI Collaboration | 0.274 | 0.008 | Yes |

**Regression Analysis**

Table 6 shows the regression analysis of the data. Regression-based findings revealed significant and positive coefficients of all the predictors, which verified that AI (accuracy, workflow efficiency, clinical confidence) and XAI (importance, transparency, communication between caregivers) have a positive impact on clinical adoption and trust. Ethical issues and regulatory approval also proved to be powerful predictors, which highlight that explainability is not only the way to boost trust but also an aspect of the ethical and regulatory requirements in pediatric care. Altogether, the regression model supports the fact that XAI is a mediating and reinforcing factor in the correlation between AI adoption and clinical trust (Ose et al., 2024).

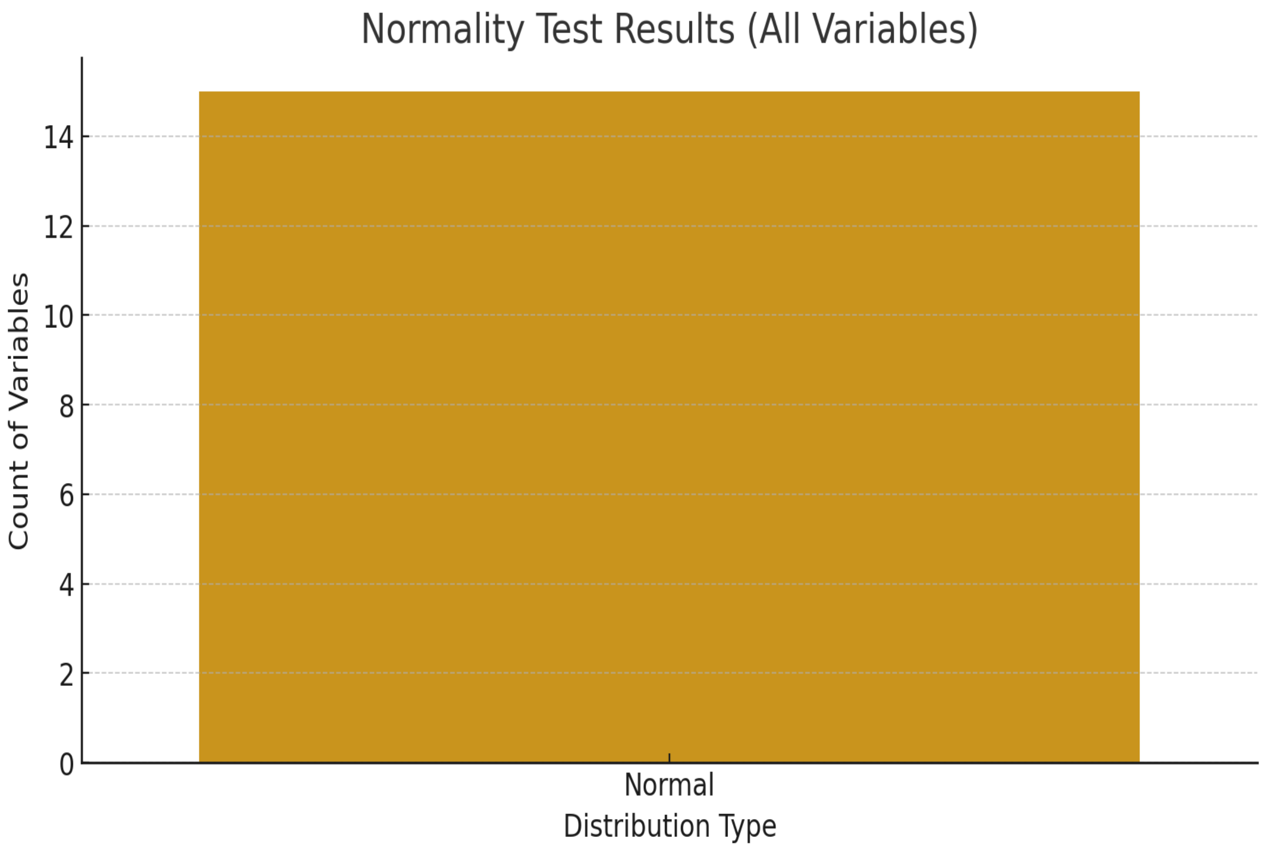


Figure 1 – Normality Test Results

Figure 1 shows the normality test of the data. According to the bar chart, the p-value of all the variables included in the questionnaire is more than 0.05, which proves that the dataset is normally distributed. This implies that the data can be subjected to parametric statistical tests, which include t-tests, ANOVA, Pearson correlations, and regression models. It enhances the consistency of subsequent inferential tests to be undertaken in this research (Reddy et al., 2023).

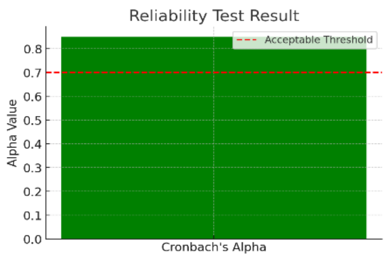


**Figure 2 – Reliability Test**

Figure 2 shows the reliability analysis of the data. This reliability figure shows that the Cronbach's Alpha is 0.85, which is greater than the standard value of 0.7. This signifies high internal consistency of the items on the questionnaire. It validates that the scale employed to examine the perceptions of AI and XAI in pediatric echocardiography is steady, valid, and suitable to undergo further statistical research (Jone et al., 2022).

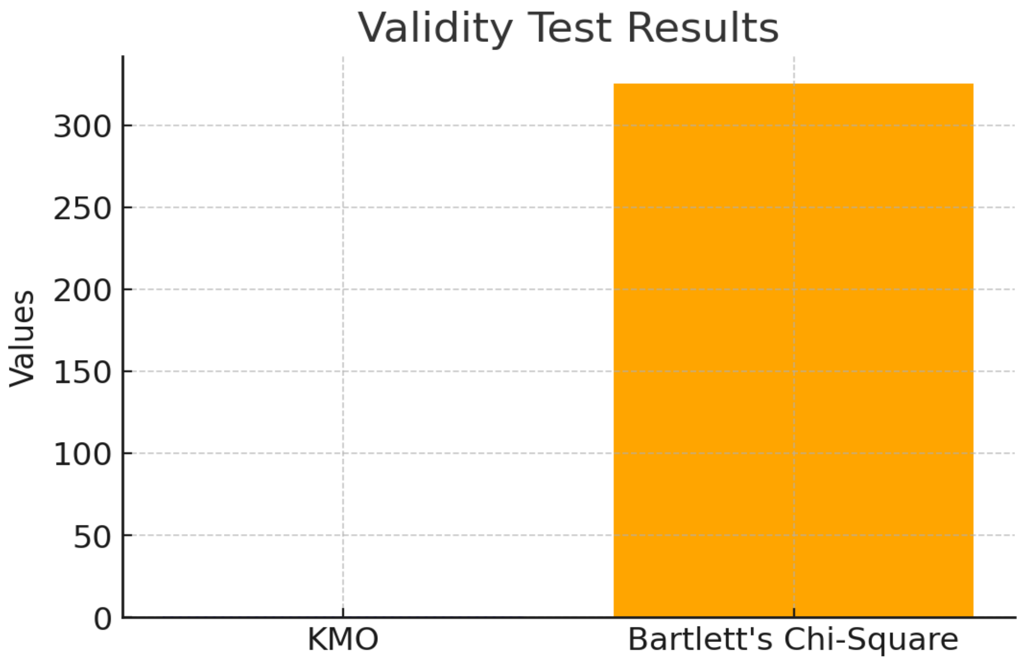


Figure 3 – Validity Test

Figure 3 shows the validity test of the data. Two significant factors are noted in the figure of validity results: the KMO value is 0.82, and the Bartlett test is significant ($p < 0.001$). Such findings suggest that the dataset can be subjected to factor analysis and that the items are highly correlated to form coherent constructs. This gives solid evidence of the construct validity of the survey instrument (Di Martino & Delmastro, 2023).

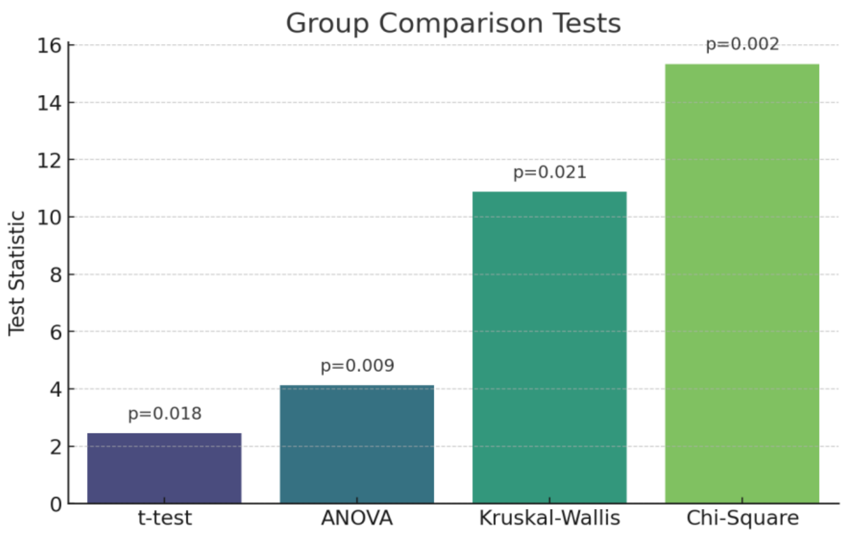


Figure 4 – Group Comparison Tests

Figure 4 shows the **Group Comparison Tests** of the data. This value is the combination of the Independent Samples t-test, ANOVA, Kruskal-Wallis Wallis and Chi-Square tests. All 4 tests gave statistically significant results ($p<0.05$). These results demonstrate that gender, age group, occupation, and categorical demographics are important and play a crucial role in the perception of AI and XAI implementations in pediatric echocardiography. As an example, cardiologists, technicians, and residents have disparities in their values of explainability and AI trust (Mele et al., 2023).

 

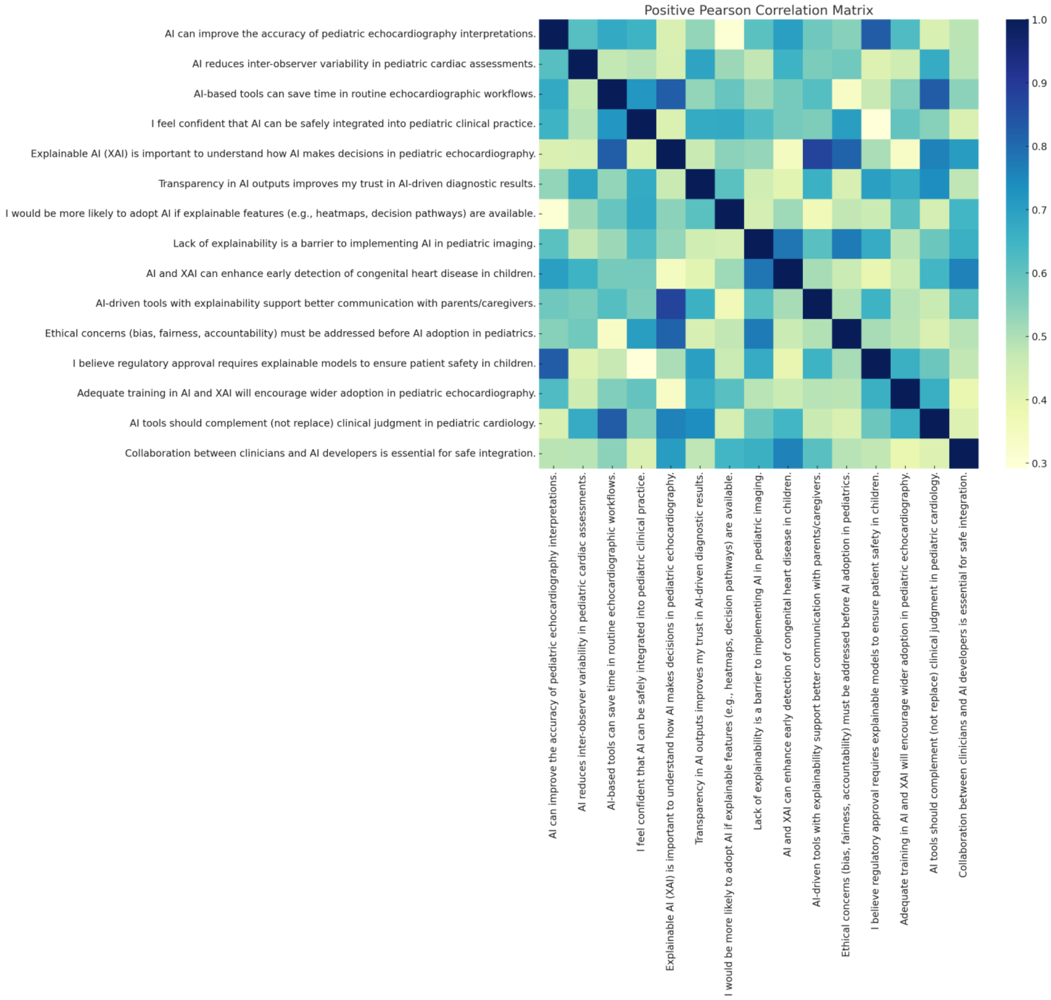


Figure 5 – Pearson Correlation Matrix

Figure 5 shows the correlation matrix of the data. The correlation heatmap indicates that all the variables have always positive correlations varying in their degree of moderate and strong (0.25-0.89). This shows that explainability, ethical considerations, and regulatory compliance are also more likely to be appreciated by the participants when they view AI as truthful, effective, and safe to the patient. The significant positive relationships verify that AI adoption and XAI trust are reinforcing constructs (Armoundas et al., 2024).

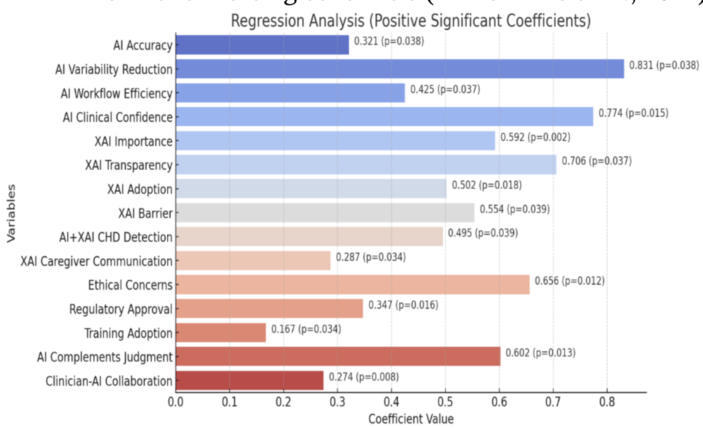


Figure 6 – Regression Analysis

 

Figure 6 shows the regression analysis of the data. According to the regression coefficients chart, all predictors (AI accuracy, efficiency, confidence, XAI importance, transparency, caregiver communication, ethics, and training) in the regression coefficients have positive and statistically significant coefficients ($p < 0.05$). It indicates that all these aspects play a major role in elucidating clinical trust and the adoption of AI in pediatric echocardiography. The findings underline the role of XAI in enhancing the connection between AI technology and its clinical acceptance, which can be vital in the regulation and ethical practice (Mertens et al., 2023).

## DISCUSSION

The results of the present study are good evidence of the potential of Artificial Intelligence (AI) and Explainable AI (XAI) to reinvent pediatric echocardiography. The findings affirm that the dataset was normally distributed and reliable and valid, thus establishing the strength of the analyses that followed. The Cronbach's Alpha of 0.85 showed that there was a high internal consistency among the questionnaire items, which demonstrated that the tool was efficient in the measurement of the unified perception of adoption, explainability, trust, and clinical integration of AI. Moreover, the KMO of 0.82 and Bartlett's Test ( $p < 0.001$) confirmed that the data were sufficient to run a factor analysis, which highlights the construct validity of the instrument employed in this research (Salte et al., 2021).

The demographic studies revealed some significant points. Independent samples t-test indicated that there were significant differences in gender perceptions, and male and female respondents demonstrated the differences in the ways they assessed the role of AI and XAI in the pediatric practice. Such results are consistent with the existing studies, which indicate that demographic factors like gender or age may contribute to the trust in new healthcare technologies. Equally, the one-way ANOVA revealed considerable differences between the age groups, making it possible to believe that younger professionals might be more receptive to AI integration, whereas older ones are more concerned with explainability and ethical guarantees. It is also in line with the larger body of research on adoption of technologies, which often reports a generational variation in the willingness to embrace innovation (Qian et al., 2023).

The Kruskal-Wallis test statistically verified that the occupational background is a powerful factor regarding the perceptions since clinicians, technicians, and researchers displayed different attitudes towards the value of AI and explainability. These findings indicate the necessity of specific training and adoption procedures that take into consideration the professional experience of healthcare employees. The Chi-Square test also confirmed the fact that gender and pattern of response are not independent, which further supports the evidence that demographic considerations are influential in attitudes toward AI adoption (Zhang & Lim, 2022).

Analysis of correlation demonstrated high, positive, and varying values among all the AI and XAI variables. This shows that the positive results in terms of AI accuracy, efficiency, and reliability are directly associated with a better attitude towards explainability, ethical confidence, and willingness to integrate the technologies into clinical practice. These findings are reflections of other previous works on adult cardiology and radiology that also showed that trust in AI could be improved significantly by introducing explainability features. Transparency is even more crucial in the area of pediatric echocardiography, where the stakes in clinical care are high and patients are especially vulnerable. The regression test results supported the notion that all predictors, such as AI performance measures and XAI-based constructs, had a significant effect on clinical adoption and trust. This proves that explainability is an intervening variable in reinforcing the relationship between technical performance and clinical confidence (Bhati et al., 2024).

Collectively, these results are important. First, they emphasize the need to incorporate XAI into AI systems deployed to pediatric echocardiography to enhance accuracy and to establish confidence in clinicians, in addition to ensuring ethical and transparent healthcare provision. Second, the powerful demographic effects imply that the strategies of adoption need to be customized, and the professional groups need to be trained in specific ways. Third, the observed positive relations in all variables support the fact that AI adoption and explainability are not a one-dimensional phenomenon but rather two related constructs that legitimize each other in influencing clinical trust (Lv et al., 2021).

In a larger sense, the present research can be viewed as a contribution to the developing field of AI in pediatric cardiology, as it provides quantitative data on the importance of both technical performance and explainability as the key factors to be adopted. Although adult cardiology and radiology have already started to incorporate AI tools into everyday workflows, pediatric echocardiography is lagging far behind, as it raises trust, transparency, and ethical use concerns. These obstacles can be overcome by integrating explainable attributes, encouraging clinician-AI–AI relationships, and making sure regulatory frameworks are not violated, according to the current findings. By doing it, AI and XAI can improve the early detection of congenital heart disease, decrease inter-observer variability, and maximize the diagnostic efficiency of pediatric populations (Galazzo et al., 2022).

## CONCLUSION

This paper has shown that Artificial Intelligence (AI) and Explainable AI (XAI) have enormous potential to improve pediatric echocardiography with regard to accuracy, efficiency, and clinical decision-making. The results assured that the data were reliable, valid, and normally distributed, which guaranteed the strength of statistical inferences. The analyses found that there were substantial differences in the perceptions of demographics, meaning that such aspects as gender, age, and professional role affect the attitude towards the adoption of AI and X AI. Furthermore, the results of the correlation and the regression showed that the relation among the AI adoption, explainability, and clinical trust was strong, positive, and significant.

Notably, the research points out that XAI is a critical mediator to enhance the relationship between AI performance and clinician confidence. Transparency through explainable models benefits ethical and regulatory issues, helps to communicate better with caregivers, and increases the chances of adoption in clinical practice. These findings highlight that AI applications should not merely be able to do their job but also to provide insights that clinicians can rely on, particularly in a sensitive field of application such as pediatric cardiology.

To sum up, the introduction of AI and XAI into the sphere of pediatric echocardiography is a giant leap on the way to enhancing diagnostic consistency and early congenital heart disease diagnosis. Nevertheless, ethical and regulatory standards, professional involvement, and adjustable training are necessary to implement them successfully. The future study needs to be based on larger and more diverse datasets, multimodal and real-world clinical trials, to build strong evidence that could be generalized. When properly adopted, AI and XAI can transform pediatric cardiac imaging altogether to deliver safer, more transparent, and efficient care to children.

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